# "Basic Skills and the Earnings of Dropouts"

John H. Tyler

Brown University
and
the National Bureau of Economic Research

Brown University Department of Economics Working Paper No. 2002-09

November 2002

I would like to thank without implication Duncan Chaplin, Jeffrey Kling, Rob Hollister, and Richard J. Murnane for comments on earlier drafts of this paper.

“Basic Skills and the Earnings of Dropouts”


Abstract

This paper tests the extent to which the accumulation of basic cognitive skills, as measured by a post-schooling math test, matter for young dropouts entering today’s labor market. Based on a sample of dropouts who were age 16-18 when administered a math test in the late 1990s, estimates indicate that a standard deviation increase in the test score is associated with 6.5 percent higher average earnings over the first three years in the labor market. These results are the first direct evidence that young dropouts in today’s economy are not relegated to jobs where basic cognitive skills are not rewarded, and they stress the importance of skill acquisition for students who may eventually drop out.



JEL Classification Codes: I20, I28, J240

Keywords: Human Capital, Dropouts, Low-Skilled Workers, Returns to Skills

“Basic Skills and the Earnings of Dropouts”

## 1. Introduction

This paper develops a simple model relating cognitive skills, schooling, and earnings and uses the model to test the extent to which basic cognitive skills matter for young dropouts. The motivation for this investigation lies in the declining economic position of low-skilled, low-educated individuals over the last twenty years. Many analysts believe the declining relative (and absolute) earnings of low skilled individuals is best explained by skill-biased technological change that has resulted in an increasing relative demand for more highly skilled workers (Bartel and Sicherman 1997; Berman, Bound, and Griliches 1994; Katz and Murphy 1992). This interpretation suggests to some that we need increased public support for programs that would raise the cognitive skill levels of the least educated individuals, particularly school dropouts. The actual benefits of such programs could, however, fall substantially below the expected benefits if shifts in the production technology of low-skilled jobs have sufficiently altered the relationship between basic cognitive skills and productivity. [1] As a simple example, consider that technological advances have essentially eliminated the ability to make change as a requisite skill requirement for counter clerks. Being able to smile while working on your feet all day may be a more important skill for today’s counter clerks than knowledge of basic math. If sufficient numbers of the least educated are working in jobs where basic cognitive skills are little needed and rewarded, then there could be an over-emphasis on

[1] For example, Autor, Levy, and Murnane (2001a) find that computerization is associated with declining relative demand for routine cognitive tasks, the type of tasks that might have been performed by young dropouts in the past. Also, see Osterman (2001), Autor, Murnane, and Levy (2001b), Murnane and Levy

cognitive skill development as a route for improving the economic conditions of low-educated individuals.[2]

To address these questions, this paper provides evidence on the extent to which basic cognitive skills mattered for young dropouts in the late 1990s. Estimates are based on a sample of dropouts who were age 16-18 when they took the General Educational Development (GED) exams between 1995 and 1998. The results indicate that dropouts who scored a standard deviation higher on the math portion of this high stakes test had average earnings over the next three years that were 6.5 percent higher than lower scoring dropouts.

## 2. A brief review of the literature on the returns to skills

An investigation of the returns to cognitive skills is a study of human capital concepts as they apply to the personal distribution of earnings. Mincer (1958) formalized this application, while Becker (1964) organized the developments in the area into a coherent theoretical structure. The early human capital empirical work was primarily focused on how to obtain unbiased estimates of the returns to schooling in the presence of unobserved ability. Most of these "returns to schooling" studies were concerned with equations similar to

$$y = bS + cW + e' \qquad (1)$$

(1996b), and Murnane and Levy (1996a) for evidence and discussions of workplace reorganization that could affect the opportunities of dropouts.

[2] Cawley, Heckman, and Vytlacil (2001) make the point that while the recent literature has focused on cognitive skills, they find that "socialization skills" are also required for success in the labor market.

where $y$ is earnings (in log form), $S$ is years of completed schooling, $W$ is work experience, $e'$ is an error term, and the OLS estimate of $b$ is interpreted as the private return to an extra year of schooling provided $\sigma_{S,e'} = 0$. The primary concern in the literature has been over unmeasured ability that is positively correlated with both $S$ and $y$, a problem first discussed in depth by Griliches (1977).

Two approaches to the "omitted ability bias problem," instrumental variables estimation and the use of identical twins to control for unobserved ability, are less relevant for the issues in this paper than is another strand in the literature.[3] One obvious approach to the problem is to introduce a control for ability into the regression. The ideal candidate would be a test score $T$ that measured "ability" without error at some point before the major effects of schooling have been felt. With the availability of $T$, the estimating equation is

$$y = aT + bS + cW + e \qquad (2)$$

where $S$ is not presumed to influence $T$ since $T$ is measured early in the schooling experience. Taubman and Wales (1973) and Griliches and Mason (1979) had early estimates of $b$ based on equation 2, where in each case the test used was an examination given to armed services personnel. Each study dealt in its own way with the fact that $T$ was measured later than optimal.[4]

---

[3] Angrist and Krueger (1991) is a well known IV paper in this area, while Taubman (1976), Ashenfelter and Krueger (1994), Ashenfelter and Rouse (1998), and Behrman and Rosenzweig (1999) are examples in the "twins" literature.

[4] In Griliches and Mason (1979) the returns to an extra year of schooling went from 5.0 percent to 4.6 percent when $T$ (in the form of AFQT score) was added to their basic earnings regression. Taubman and Wales (1973) estimated an 11 percent return to moving from a high school diploma to a B.A., controlling for ability, but they do not provide estimates where $T$ is omitted for comparison.

While studies based on equation 2 are related to the topic at hand, the focus in 2 is still on using $T$ to obtain good estimates of $b$, the returns to schooling. A related but distinct strand of the human capital literature is composed of studies that are interested in estimates of the effect of ability on earnings, controlling for the separate effects of schooling. These studies usually estimate some form of equation 2, with an important difference. In these studies $T$ is ideally measured after rather than before schooling is completed, and hence it is assumed that years of schooling, $S$, affects measured skills, $T$, and the focus is on estimates of $a$ rather than $b$. To clarify the following discussion, designate this measure of skills as $T^+$ to indicate that it is measured after the completion of schooling. Note that if $T^+$ captures all of the human capital components of schooling, then $S$ will contain only the portion of schooling that is associated with credentialing or signaling (Spence 1973). On the other hand, if we think that the human capital acquired through schooling is best described as a vector of skills, and that $T^+$ only captures specific elements in the vector, then $S$ measures the remaining elements of the human capital vector along with the credentialing component of schooling. Using $T^+$ instead of $T$, we have equation 2a

$$y = aT^+ + bS + cW + e \qquad \text{(2a)}$$

as conceptually distinct from equation 2.

One of the first studies explicitly interested in estimates of $a$ in equation 2a was Boissiere, Knight, and Sabot (1985). Using a data set containing post-schooling measures of basic numeracy and literacy, they found the estimate of $a$ to be large relative to the estimate of $b$. Their interpretation of their findings is that the human capital portion of schooling, measured by $T^+$, is a more important determinant of earnings than the signaling or credentialing portion of schooling, measured by $S$. In an interesting use of the National Adult Literacy Survey (NALS), Ishikawa and Ryan (2002) decomposed $T^+$ into the portion acquired through schooling and that acquired "elsewhere" as defined by parental background, number of books in the home, presence of a library card, etc. They found skills acquired through school to be more important in determining earnings than the skills acquired "elsewhere." Murnane, Willett, and Levy (1995) estimated a version of equation 2a over cohorts that entered the labor market eight years apart and found estimates of $a$ to be substantial and increasing between 1978 and 1986. Other work has looked at returns to various types of coursework (Altonji 1994; Mane 1999) or to college credits (Kane and Rouse 1995), conceptual equivalents to $T^+$.

Many of the most recent investigations of the effects of cognitive skills on earnings have been motivated by Hernnstein and Murray's survey and interpretation of a vast body of research relating test scores to a wide range of social outcomes (1994). Their controversial conclusions regarding this research prompted studies that closely examine the relationships between skills, schooling, and outcomes, along with related econometric issues. In particular, Cawley et al. (1997; 2001) and Heckman and Vytlacil (2001) discuss and illustrate the difficulty in estimating equations similar to 2a in panel data. A lesson from that research particularly relevant for this paper has to do with the difficulty in estimating the separate effects of schooling ($S$) and cognitive ability ($T^+$) in data where there are wide ranges of schooling and ability. The problem arises from the high correlation between schooling and ability, and typically results in empty schooling-ability cells (e.g., there are no high ability types with very low levels of education in most data). The implication is that ad hoc parametric assumptions must be placed on the data, assumptions they are able to reject in their data. I address this issue as it pertains to the data used for this paper when results are presented.

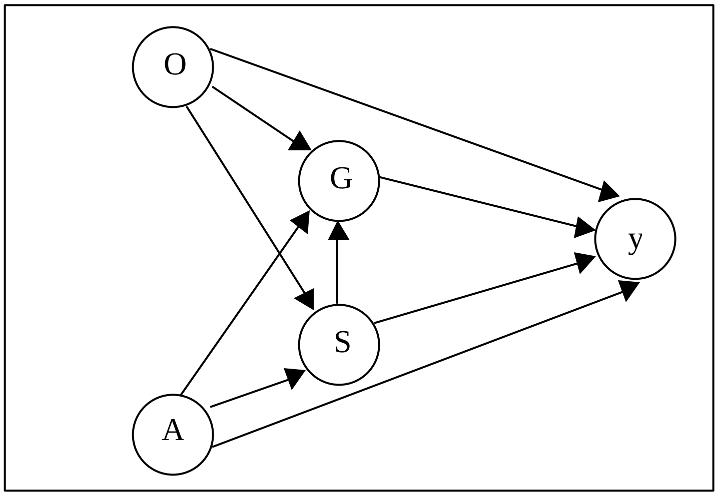
How cognitive skills, schooling, and earnings interrelate is an obviously important and well-studied topic. The human capital research to date has little to say, however, about equation 2a as it relates to very low skilled individuals, nor has the literature generated results that would let us draw inferences about the returns to cognitive skills for this group.[5] This investigation addresses that issue by examining the extent to which basic cognitive skills matter for the least skilled individuals in the labor market—young high school dropouts. These are individuals with low levels of both schooling and work experience. A second feature of this paper is that it uses information on individuals who entered the labor market as recently as 1999, while papers in the current human capital literature rely on individuals who entered the labor market in 1992 or earlier. To the extent that the economy changed for the low-skilled, the more recent labor market outcomes provide better information regarding the importance of basic cognitive skills for young dropouts.

### 3. A simple model relating basic skills to earnings

I assume that basic skills are influenced by three distinct, but related factors, and that these factors, along with basic skills, affect earnings. The relationships are shown in Figure 1.

[5] One exception is Tyler, Murnane, and Willett (2000a), but the results in this paper only suggest that the basic skills of dropouts are associated with higher earnings, no formal inferences can be drawn.

Figure 1.




In Figure 1 $y$ is earnings, $S$ is years of schooling, G is basic cognitive skills, $A$ is innate ability, and $O$ is a vector of "other" factors that may affect schooling level, cognitive skill development, and later earnings. Examples of elements in $O$ are parental education, number of books in the home, home stability, etc. I assume that all of the variables in Figure 1 are positively correlated. That is, higher levels of both ability and other factors lead to higher levels of schooling, cognitive skills, and earnings; more years of schooling leads to greater cognitive skill development and higher earnings; and, higher levels of cognitive skills result in higher earnings.

The system of equations that underlie Figure 1 and focus our attention on the empirical work at hand are given by

$$S = a_0 + a_1A + a_2O + e_1 \tag{3a}$$

$$T^+ = b_0 + b_1A + b_2O + b_3S + e_2 \tag{3b}$$

$$y = c_0 + c_1A + c_2O + c_3S + c_4T^+ + c_5W + e_2 \tag{3c}$$

$$T^+ = G + v \tag{3d}$$

where $e_1$, $e_2$, $e_3$, and $v$ are error terms and equation 3d makes explicit the assumption that test score $T^+$ measures true skill level $G$ with error.

Equation 3c illustrates the problem in estimating equation 2a when the model relating ability, skills, schooling, and earnings is allowed to be as complex as that represented in Figure 1. In particular, equations that omit measures of $A$ and $O$ will misestimate both $a$ and $b$ in 2a. The problems have been recognized and addressed to varying degrees in the literature. Boissiere, Knight, and Sabot (1985) employed a data set with a plausible measure of $A$, but their model and estimates did not allow for the possibility of $O$. Ishikawa and Ryan (2002), on the other hand, have measures of $O$, but no good measures of $A$. Few other papers in the "returns to skill" literature have explicitly addressed omitted $A$ or $O$.[6] Furthermore, even when $A$ or $O$ is available, one would expect attenuation bias in the OLS estimate of $c_4$ in equation 3c as a result of the measurement error expressed in 3d.

Obviously, the demands on the data in this extended human capital model are substantial, given the need to control for $A$ and $O$ and the potential for measurement error bias. This paper makes no claims at overcoming all of the potential problems raised by this extended model. The empirical work does, however, reflect the issues raised by the model and addresses them as best as possible given the available data. To that end, variants of equation 3c that include measures of $A$ and $O$ will be estimated and provide the primary results of the paper. The variables that will be employed for $A$ and $O$ are admittedly less than perfect, but comparisons between models that do and do not include these variables will at least provide a sense of the importance of the omitted variable

---

[6] It is worth noting that no papers in the returns to skill literature have found convincing instruments for $T$.

problem. Also, I will use a data set where attenuation may be less of problem than would otherwise be the case.

**4. The Data**

The empirical task of this paper is to estimate the returns to the basic skills that young dropouts carry into their first jobs in today's labor market; we want to estimate 3c using an appropriate sample of young dropouts who are in their first years in the labor market. Further, we want these first years to be measured as recently as possible since technological advances and workplace reorganization may have altered the entry-level jobs in which young dropouts are first employed.

Data that meet these and other objectives come from a sample of dropouts who all attempted the General Educational Development (GED) exams in Florida between 1995 and 1998 when they were ages 16 to 18. While not a random sample of dropouts, data on GED candidates offer distinct advantages. First, these data contain very recent labor market information on a large sample of dropouts, along with a measure of basic cognitive skills and information on years of completed schooling. Other data sets, such as the NLSY, contain labor market information, a measure of skills, and information on schooling, but none have information on dropouts who entered the labor market in the late 1990s.[7]

A second reason for using data on dropouts who attempt the GED exams is that the data contain at least a partial measure of innate ability, *A*. Individuals who fail the GED

[7] The NLSY97 data set, based on a nationally representative survey of 9,000 youths who were 12-16 years old in December 1996, will be the exception to this statement as the 4th and 5th rounds of that survey becomes available.

exams can retake any of the five tests in the battery. I will use an indicator of multiple testing as a measure of otherwise unobserved ability. The assumption is that given two individuals with the same (final) GED test score and years of schooling, the individual who had to attempt the exam multiple times to obtain that score started out with lower ability than did the individual who attained that score on the first attempt.

These data also contain information on race/ethnicity, variables that I will employ as a partial measure of *O*. The assumption here is that variation in racial/ethnic background picks up variation in factors such as parental education, home environment, and other elements that may be in the *O* vector. The author's examination of dropouts in the NLSY supports this proposition. For example the mothers of white dropouts in the NLSY have 11.5 years of schooling on average, compared with 10.8 for black mothers, and 7.9 for Hispanic mothers. (The figures are similar for the fathers of dropouts.) The fathers of white dropouts were also more likely to be working when the respondent was age 14 than were the fathers of black or Hispanic dropouts. And, white dropouts were much more likely to have magazines, newspapers, and library cards in the home when they were age 14 than were the other groups.

The variables I use for *A* and *O* are admittedly less than perfect, and their limitations should be recognized in the results to come. I will present estimates that do and do not include these variables so that the reader can make judgements as to the severity of the omitted variable problem.

A third advantage of using data on GED candidates is that we expect measurement error bias to be less in this group than in the general population of dropouts. School dropouts are likely to have an above average aversion to academic endeavors such as taking standardized tests, particularly if there are no stakes attached to the tests. As a result, they may bring systematically lower levels of motivation to an "achievement" type test. This is a measurement error problem that manifests itself by shifting the mean of the measurement error distribution to the left and by increasing its variance over what we would have if everyone gave their best effort.[8] For dropouts who desire this credential, the GED is a high stakes test, and I assume that GED candidates bring a higher level of motivation to the test than do dropouts in the general population taking a no-stakes test. That is, I assume that GED candidates are drawing their test errors in equation 3d from a distribution with a smaller variance than are dropouts asked to take a no-stakes test. As a result, estimates of $c_4$ in equation 3c based on GED candidates will have less attenuation bias.[9]

A fourth potential advantage in using these data is that the earnings information is based on state administrative unemployment insurance (UI) records rather than from self-reports. There are tradeoffs between using UI earnings records versus records from survey data such as the NLSY. On the one hand, state UI data contain no information on hourly wages, as does the NLSY. While the wage offer to an individual reflects the market demand for the skills of that individual, the quarterly earnings found in UI data are a function of both demand and labor supply. Thus, conceptually, wages may be preferred over earnings when measuring returns to skills. However, wage information

[8] One can think of a shifting of a normal measurement error distribution, or one may think that systematic lack of effort skews a standard measurement error distribution to the left, shifting the mean and increasing the variance. The standard OLS measurement error analysis can proceed with a skewed measurement error distribution under the standard assumptions regarding the signs of the covariances involved.

[9] If it is the case that in the general pool of dropouts, those with more ability try harder and score closer to their true score than those with lesser ability (i.e., $s_{G,v} \neq 0$), one can still show that attenuation bias is less

obtained from survey data can suffer from problems such as non-random sample attrition and inaccuracy in self-reported wages that compromise the conceptual ideal. Additionally, wages in most of the available surveys are recorded (at best) only annually, while the UI records provide labor market information every quarter. For these and other reasons state administrative UI data are an increasingly utilized data source in empirical studies in labor economics.[10]

The Florida GED data contain demographic and test-score information on the universe of dropouts in Florida who last attempted the GED exams between 1995 and 1998. The measure of skills that I will use is the GED math test score. I focus on math skills for two reasons. First, others have found math skills to be more strongly related to labor market outcomes than are test scores in other subject areas.[11] Second, in order to do well on the GED math test one also must be able to read at a basic level and follow directions, whereas to do well on a reading test one need not know any math. The distribution of raw GED math scores over the possible range of 20 to 80 is shown in Figure 2. These scores show evidence of being drawn from a normal distribution, though there is evidence of possible ceiling effects.

< Figure 2 about here >

---

in the GED candidate pool if $s^2_v$ for GED candidates is smaller than $s^2_v$ for dropouts in general and if $s^2_v < s^2_G$ for both groups.

[10] For an example of the use of UI date see Jacobson, LaLonde, and Sullivan (1993). UI earnings are not available for out-of-state earnings or for jobs that are not usually covered by the UI system, such as self-employment, work which may be "off the books" such as domestic service or informal child care, or for employers who do not report earnings. Thus, UI earnings may understate "true" earnings. A comparison of data from UI and data with more complete coverage from the Social Security Administration (SSA) found that average earnings from SSA data were about 25% higher. Self-reported earnings for adult men were 30% higher than UI reports, with the additional difference apparently due mainly to uncovered jobs rather than out-of-state jobs(Kornfeld and Bloom 1999).

Information on quarterly earnings is available from the first quarter of 1995 through the last quarter of 1999. Individuals who had no quarterly earnings in a given quarter were assigned earnings equal to zero. Earnings information for the sample of GED examinees was obtained by linking the GED test files with quarterly earnings records collected by Florida's Unemployment Insurance system.[12] Florida was chosen for this study because of the opportunity to produce such a data file. The Appendix provides more information on the GED exams and summary statistics for the analytic sample are found in Appendix Table A1.

## 5. OLS Estimation

To estimate the returns to the basic math skills of dropouts I fit a series of models based on equation 3c. The estimating equation is

$$\begin{aligned} y_{ijt} &= c_j + c_1 A_{ij} + c_2 O_{ij} + c_3 S_{ij} + c_4 T_{ij}^{+} + c_5 W_{ijt} \\ &\quad + c_6 X_{ij} + c_7 M_t + e_{ijt} \end{aligned} \tag{4}$$

where,

*i* indexes individuals and *j* indexes the test-cohort defined by the year and quarter in which the GED was last attempted, and $t \in [1,2,\ldots,12]$ indexes the quarter after the GED attempt in which earnings are measured,

*y* = log quarterly earnings,

*A* = a dummy variable indicator of whether or not individual *i* in cohort *j* attempted the GED math test more than once,

---

[11] See for example, (Glazerman, Schochet, and Burghardt 2000; Murnane et al. 2000; Murnane, Willett, and Levy 1995; Tyler, Murnane, and Willett 2001).

$O$ = race/ethnicity dummy variable indicators,

$S$ = years of completed schooling prior to dropping out,

$T^{+}$ = a vector containing the normalized GED math test score and its square—the score is normalized to have a mean of zero and standard deviation of one,

$W$ = a vector of work experience whose elements are the number of quarters worked previous to time $t$ and the square of the number of quarters worked previous to time $t$,[13]

$X$ = a vector of time-invariant personal characteristics or factors that may influence $y$, including gender, age at the time of the last GED attempt, and whether or not the individual possesses a GED,[14]

$M$ = a set of dummies indicating the year and quarter in which $y$ is measured, and

$c_j$ captures test-cohort fixed effects where the cohorts are defined by the year and quarter in which the GED was last attempted.

Equation 4 is estimated using Ordinary Least Squares on a stacked person-quarter data set with each individual potentially contributing from one to twelve quarters of earnings data.[15] Standard errors are adjusted to account for the within-person correlation of the error term across time.

---

[12] The file linkage was done by the Florida Education and Training Placement Information Program (FETPIP). All earnings are deflated to 1999 constant dollars using the CPI-U deflator.

[13] Evidence of having worked is provided by the presence of non-zero earnings in a quarter.

[14] I control for GED status since other research has found acquisition of a GED to be associated with higher earnings, net of GED test scores (Tyler, Murnane, and Willett 2000b). On the other hand, Cameron and Heckman (1993) find a positive, but not statistically significant, effect of the GED on earnings.

[15] Not all individuals have a full twelve quarters of earnings information in the data. For example, since UI earnings were available only through the last quarter of 1999, individuals who tested in the last quarter of 1998 contribute only four quarters of earnings to the data.

## 6. Results

As a starting point, Figures 3a and 3b give the raw mean positive quarterly earnings by gender and upper versus lower GED math quartile for quarters 1-12 after the GED exam. The lessons from these two figures are that the earnings of young dropouts increase with time during their first quarters in the labor market and that higher scoring dropouts earn more than lower scoring dropouts. This latter result based on unconditional comparisons sets the stage for the analysis.

As a first step, I estimate the education production function represented in equation 3b to provide a sense of the relative importance of *S*, *O*, and *A* in explaining variation in math test scores. Column 1 of Table 1 gives the estimates and $R^2$ from a regression of the normalized math score on an indicator for gender and age at the time of the GED test, controlling for test-cohort fixed effects. This minimum set of variables explains only one percent of the variation in GED math test scores. In the second column, years of schooling is added to the regression, and while still relatively small, the $R^2$ goes up substantially relative to the first column. The estimate indicates that each additional year of schooling completed before dropping out is associated with about a fifth of a standard deviation increase in the GED math score.

Indicators of race/ethnicity are added to the regression in the third column. To the extent that racial/ethnic groups differ systematically in parental education, home educational resources, environments favorable to education development, and other elements one might think are in the *O* vector, then race/ethnicity proxies for more complete measures of *O*. Of course, these variables may also be measuring factors in the education production function other than *O* such as variation in school quality. The inclusion of these variables doubles the explanatory power of the regression from the previous column so that about 8 percent of the variation in math scores are explained by the variables in the column 3 regression.

<Table 1 about here>

The indicator for multiple testing as a measure of ability is added to the last regression. The addition of this variable increases $R^2$ by another forty percent. Also, individuals who took more than one math test have final test scores that are over a half a standard deviation lower than individuals who only tested once.

Table 1 offers only suggestive evidence that the variables used to control for innate ability and "other" factors that influence cognitive skill development are good measures of the two constructs, *A* and *O.* In fact given the substantial amount of variation in test scores left unexplained, there is equally compelling evidence that substantial components of *S, A,* or *O* are still omitted, and as a result there is reason to be cautious in interpreting the results to come. The directions of the estimated relationships in the table are what one would expect, however, if attempting the tests more than once captures some portion of *A* and if race/ethnicity captures some portion of *O.* Also, the estimates on the relevant variables are all of a size to indicate that these are important predictors of math score. Nevertheless, to the extent that any remaining unexplained variation in *A* and *O* is correlated with both the math score and earnings, the estimated returns to basic skills will be biased.

The analysis now focuses on the central question concerning the estimated returns to basic math skills for dropouts. The columns across Table 2 display results from nested versions of equation 4 so that the importance of including or excluding the measured variables in *A* and *O* can be examined. The first column of Table 2 gives OLS estimates of equation 4 omitting both the race/ethnicity indicators that I use as measures of *O* and the multiple test indicator that I use as a measure of *A*. The interpretation of this column is that a one standard deviation increase in *math* at the mean (of zero) is associated with a 7.7 percent increase in quarterly earnings during the first three years of employment.[16] We expect, however, this to be an a biased estimate given the omission of *A* and *O*.

<Table 2 about here>

Estimates in the second column are from a model to which racial/ethnic indicators have been added to control for *O*. Of course, controlling for race/ethnicity in earnings regressions is standard practice. Though not always articulated, the rationale is often to "control for labor market discrimination" or "unobserved factors that affect productivity," and, depending on the study, we either are or are not interested in interpreting the estimated coefficients on the relevant dummy variables. I simply note that the interest here is on their role as elements of *O* and their ability to control for variation in factors other than ability or schooling that may influence basic cognitive skill development. There is no attempt to interpret the estimated coefficients on these variables in the earnings equation, though I present them for the reader's convenience.

When racial/ethnic indicators are included, the estimated returns to the math score at the mean fall by about 15 percent. Interestingly, very little additional variance in quarterly earnings is explained by the addition of these variables. The estimated returns to

[16] Calculated as $e^{0.074}-1$, since the squared term on the math score drops out when the calculation is at the mean test score.

math skills in this column may still be biased since we have included no controls for innate ability that may affect skills independently of years of schooling.

In column three the indicator for multiple attempts at the GED is included. The inclusion of this variable has only a small effect on the estimated math score coefficient. In this full model we estimate that a standard deviation increase at the mean in the basic math skills of dropouts is associated with quarterly earnings that are 6.5 percent higher.

In investigations based on a random sample of the population, the work of Cawley et al. (1997) indicates that the returns to cognitive ability are different across race and gender. These results do not appear to generalize to young dropouts, at least young dropouts who are GED candidates. I fail to reject the null hypothesis that the estimated coefficients on *math* and $math^2$ are jointly the same for whites and blacks ($p = 0.16$), for whites and Hispanics ($p = 0.39$), or for males and females ($p = 0.54$). Following the findings of Heckman and Vytlacil (2001), I also examined the possibility that the effects of math scores and years of schooling on earnings were non-linear by creating math quintile and years of schooling dummy variables and their interactions. I was unable to reject the null that the coefficients on the math score quintile by year of schooling interactions were jointly zero ($p = 0.44$), and an examination of the coefficients on the quintile dummies in a regression not including the interactions offered no evidence against the linear plus quadratic specification of equation 4. I also note that the cells formed by the interactions all had substantial numbers of observations. That is, in the GED-candidate data there are individuals with low levels of education who score relatively high on the GED math exam and vice versa, addressing the concern raised by

Heckman and Vytlacil (2001) over estimating equations similar to 4 in the general population.

Cawley, Heckman, and Vytlacil (2001) find that "socialization skills" are important determinants of labor market outcomes, along with cognitive skills. This raises a concern about omitted variable bias in the estimates of Table 2. In particular, if there is a positive correlation between "socialization skills" and basic cognitive skills among dropouts, then the estimates in Table 2 will be upwardly biased. To examine the potential magnitude of this problem I examined the relationship for eventual dropouts between nine "socialization skill" type variables and a test of basic math skills given to 10th graders in *High School and Beyond* (HSB) data.[17] In a regression of the 10th grade math score in the HSB on the nine socialization variables, only 0.003 of the variation in the test score was explained, and none of the socialization skills variables were statistically significant. When gender, race/ethnicity, highest grade completed, and parental education variables are added to the regression $R^2$ increased to 0.12, none of the socialization skill variables were significant at the 0.10 level or lower, and I was unable to reject the null that the coefficients on the socialization skill variables were jointly zero ($p = 0.89$). The evidence from *High School and Beyond* is that while socialization skills may affect earnings, they do not appear to be systematically related to the basic math skills of dropouts. This is at least suggestive evidence that the estimates in Table 2 are not simply picking up correlation between math test scores and non-cognitive skills related to earnings.

---

[17] The variable descriptions are listed in the Appendix. The regression results from this analysis are available from the author upon request.

As mentioned earlier, there are reasons to exercise caution in interpreting this estimate as the causal effect of basic skills on the earnings of young dropouts. Ultimately, this investigation is not able to rely on a clear source of exogenous variation in basic cognitive skills. However, given that the estimated return to the GED math test changed little when the available controls for *A* and *O* were added in the second and third columns, we conclude that for young dropouts either omitted ability and “other” factors that influence basic skill development are not substantially important, conditional on the other variables in the regression, or that the available controls are very poor measures of *A* and *O*. Unfortunately, there is no way to distinguish between these two possibilities in the data.

Given that a standard deviation increase in math scores is associated with an estimated 6.5 percent increase in quarterly earnings, it is worth examining the distribution of math skills across demographic groups. Table 3 gives the distributions across math quartiles by gender and race/ethnicity. The disturbing facts from this table are that one half of young black dropouts, male and female, scored in the bottom quartile of the GED math test score distribution and that a third of all Hispanic female dropouts scored in the bottom quartile.

<Table 3 about here>

While the use of GED candidates to estimate the early-market returns to skills has the aforementioned benefits, there are at least two limitations of these data. First, the results based on a sample of GED candidates in Florida may not be generalizeable to the broader population of dropouts. Second, while we have data that will let us examine the early returns to basic skills, there is no information in these data on how these returns change with labor market experience. I address these concerns by using data on dropouts in the NLSY. NLSY data do not provide the ideal comparisons for at least three reasons. First, late-teen dropouts in the NLSY entered the labor market in the early 1980s when the low-skilled, entry-level job market could have been substantially different than today. Second, the measure of basic cognitive skills in these data, the AFQT, may be measuring different skills than the GED math exam. Third, there is no measure of innate ability, *A*, in the NLSY data. Nevertheless, dropouts in the NLSY provide the best comparison group available.

Lacking information in the NLSY on quarterly earnings, I use log hourly wages (in 1999 constant dollars) at the current/most recent job as the dependent variable. To match the GED candidate sample as closely as possible, the NLSY sample is restricted to those respondents who were age 16-18 when they took the AFQT in 1980 and who had not finished high school by 1998. While the NLSY data contain no good measure of *A*, there are potentially much better measures of *O* in these data, including parental education and employment, number of siblings, whether or English was the primary home language, and the presence of magazines, newspapers, and a library card, all measured when the respondent was 14 years of age.

The age-adjusted AFQT score was standardized using the entire NLSY sample of 12,686 respondents. The transformed variable has a mean of zero and a standard deviation of one. Figure 4 shows that not surprisingly, the great majority of dropouts in the NLSY fall in the left-hand tail of the AFQT distribution. Figure 4 also demonstrates the non-normality of the AFQT distribution among dropouts in the NLSY.

<Figure 4 about here>

Estimates from regressions based on equation 4 using the NLSY data are in Table 4. The primary differences between the GED-candidate models and the NLSY-based models are that the latter contain better measures of *O*, but no measure of *A*.[18] The OLS estimates in the first columns of Table 4 were obtained by stacking data from survey years 1981, 1982, and 1983, the three years immediately subsequent to taking the AFQT. Standard errors are corrected for the correlation of individual errors across years.

<Table 4 about here>

The estimated return to the AFQT score in column 1 of Table 4 is 0.031 and not statistically significant. This is about half the size of the estimated average return to the GED math score presented in Table 2. These differences are consistent with any of the following non-mutually exclusive explanations: (1) The returns to the basic skills of dropouts have gone up over time (Murnane, Willett, and Levy 1995); (2) The GED math test and the AFQT measure different skills that have different returns in the market; (3) The expanded list of variables available for the *O* vector in the NLSY reduce bias due to omitted variation in *O*; (4) As predicted, there is more attenuation bias associated with the AFQT because it is a no-stakes test for the dropouts who take it. Regardless of the explanation for the difference in the estimates, it remains that the estimates from the two data sets are of the same order of magnitude. Thus, we can at least say that the NLSY-

[18] While I include GED holders in all NLSY regressions, I do not control for the independent effect of the credential. The reason is that in these data any GED acquisition occurs after the measuring the AFQT score, rather than concurrently as in the Florida data on GED candidates. If one mechanism through which a higher AFQT score may affect earnings is via GED-acquisition then it would be inappropriate to control for the credential. The results are very similar across models that do control for GED status.

based estimates offer no strong evidence against the ability to generalize inferences based on GED candidates.[19]

An advantage of the NLSY data is that they allow us to examine the extent to which returns to basic skills of dropouts might change with labor market experience. To examine this question I stack ten years of NLSY hourly wage data, 1981-1990 and allow for a linear time trend in the returns to the AFQT score. The estimates in column 2 of Table 4 indicate that the returns to the AFQT are around 1 percent per standard deviation increase in the AFQT in the very first year (and statistically insignificant), and that they grow at almost one percent per year for the first ten years young dropouts are in the labor market. This is consistent with models predicting that the returns to skills should grow with labor market experience (Altonji and Pierret 1996; Farber and Gibbons 1996).

## 7. Discussion

Given the lack of clearly exogenous variation in either the GED math score or the AFQT, it is difficult to attach a purely causal interpretation to the estimated returns thus far discussed. The results are, however, consistent with a human capital explanation that dropouts earn more if they know more, even in the low-level jobs that facilitate a dropout's entry into the labor market. The findings presented here suggest that programs aimed at increasing the basic cognitive skills of dropouts could impact earnings during their first years in the labor market. How large are the lifetime earnings gains we might expect from such a program? As a starting point, assume that the earnings of dropouts in the current labor force are a good approximation of the age-earnings profile that the

[19] When the square of the AFQT is entered in the model of column 1 in Table 4 the estimates (and standard errors) on the linear and quadratic AFQT coefficients are 0.033 (0.021) and −0.038 (0.019) respectively.

average dropout who entered the labor market in 1999 would face over his lifetime.[20] Also, to simplify the discussion, I continue with the assumption that the basic math skills measured on the GED math test proxy for basic cognitive skills in general.

The estimates in this paper indicate that during the first years in the labor market a young dropout can expect earnings increases of about 6.5 percent per standard deviation increase in basic skills, and that this return will grow by about one percent annually for the next ten years. For this exercise, I assume that the returns to skill continue to grow at a one percent annual rate until the dropout is 50 years old and remain constant thereafter.

What is a reasonable expectation regarding the impact on skills of programs directed at dropouts? There have been very few rigorous evaluations of programs that might raise the skills of dropouts. One exception is Job Corps, where an experimental evaluation found that eight months in Job Corps led to increases in quantitative literacy scores that were 0.10 of a standard deviation higher than the skill gains experienced by the control group (Glazerman, Schochet, and Burghardt 2000). Job Corps is targeted at disadvantaged youth and has components that are not directly focused on skill-enhancement. Therefore, it is plausible that a dedicated skills-enhancement program directed at dropout youth—not all of whom are as disadvantaged as Job Corps applicants—could produce gains larger than 0.10 of a standard deviation. If we assume that a dedicated skills-enhancement program could raise the basic skills of dropouts by 0.25 of a standard deviation, and we couple this assumption with the initial and annual growth in the returns to skills just discussed, we get the elevated age-earnings profile displayed in Figure 5. The "untreated" lower profile in Figure 5 is simply the weighted

[20] This part of the analysis draws on Krueger (2000).

combination of the male and female age-earnings profiles in 1999.[21] Assuming a three percent discount rate, the present discounted value of the stream of earnings differences between the two curves in Figure 5 is $16,343.

As with any cost-benefit analysis, the results from this one are only as good as the assumptions upon which they rest. Alternative assumptions about the impact of the skills program, the rate of annual productivity growth, or the discount rate would generate more or less optimistic estimates, holding other factors equal. Estimates based on alternative assumptions about these three factors are displayed in Appendix Table A2. $16,343 falls roughly in the middle of the range of estimates in this table.

<Figure 4 about here>

Heckman (2000) noted in his survey of interventions aimed at disadvantaged adolescents, that while sustained interventions can positively impact the learning of in-school youth, interventions for dropouts appear to be much less successful. The challenge, therefore, is finding or developing programs that cost less than $16,000 per person and that can increase the skills of dropouts by a quarter of a standard deviation.[22] Of course, this formulation of the problem ignores the positive externalities that may be associated with increasing the skills of young dropouts. To the extent that higher cognitive skills translate into lower crime participation rates, increased health, and decreased dependence on public assistance over a lifetime, $16,300 underestimates the

---

[21] The weights are the proportions of males and females in the dropout pool at each age.

[22] By comparison, eight months in Job Corps, a largely residential program, costs about $16,500 per participant. But again, there are many components of Job Corps that are not directly related to increasing the cognitive skills of participants.

total present discounted value to society of the benefits that would result from increasing dropouts' basic cognitive skills.

Like most such exercises, the "back of the envelope" calculation in this section rests on several contestable assumptions and is, therefore, welcoming to criticism. On more solid ground, however, are two lessons from this paper—one already known and one predicted by the canonical human capital model, but not yet documented. The first is that more than ever, dropping out of school is a bad economic decision. The very low quarterly earnings of GED candidates in Table A1 and the very low age-earnings profiles of dropouts in Figure 4 are simply reminders of what has been known for some time: dropouts are at a severe disadvantage in today's economy.[23] The second message from the paper is less well established in the literature. That lesson is that an economy that has moved from an industrial base to a technologically-advanced, information-related base has apparently *not* relegated young dropouts to jobs where basic cognitive skills are unimportant from a productivity standpoint. The skills that young, low-skilled individuals take into their first jobs matter. As a result, the joint investment that schools and students make in developing basic skills matters—even for students who will dropout before gaining a diploma.

[23] For example, see Krueger (1998) for the time trend of the ratio of the median weekly wages of those with exactly a high school diploma to dropouts. According to Chart 6 in that paper, the ratio increased from about 1.18 in 1979 to 1.40 in 1995.

Appendix

## The GED Exams

Dropouts desiring a GED must attain state mandated minimum scores on the five GED tests, as well as a minimum total score on the five tests.[24] Thus, there is a strong incentive to do well on the tests for dropouts who desire a GED. All of the GED tests have a multiple-choice format, and the writing test also requires examinees to write a short essay. With some minimal restrictions individuals who fail any of the tests can retake those tests.

Appendix Table A1 presents separate summary statistics on the analytic sample by gender. There are slightly more female than male dropouts in the sample, and each gender group is about three-quarters white, non-Hispanic, eight percent black, non-Hispanic, 14 percent Hispanic, and three percent “other race/ethnicity.” About 90 percent of the sample successfully obtained their GED. Twelve percent of the males and eleven percent of the females attempted the GED more than once. The median age at the time skills were measured was about 17 and most individuals completed about 9 or 10 years of schooling before they dropped out. Males tended to score higher on the math tests than females.

< Appendix Table A1 about here>

In the last rows of the table males in the lower quartile of the GED math score distribution have mean positive quarterly earnings three years after testing that are 16

[24] The passing thresholds are different across the states. In Florida the requirements are at least a 40 on each of the five tests and a total score of at least 225.

percent lower than the mean earnings of male dropouts in the upper quartile of the math score distribution. The difference for females is 19 percent.

## *High School and Beyond* "Socialization Skills" Variables

The variables in the *High School and Beyond* survey that were used in the analysis of the relationship between socialization skills and math scores were:

1) Score on a diagnostic designed to measure the respondent's (R) self concept.

2) Perception of popularity: indicator variable that equals one if R perceives of him/herself as somewhat or very popular with classmates.

3) Socially active: indicator variable that equals one if R perceives of him/herself as somewhat or very socially active.

4) Troublemaker: indicator variable that equals one if R perceives that classmates see him/her as very much or somewhat of a troublemaker

5) Job application skills: indicator variable that equals one if R believes that he/she knows how to apply for an office job in a big company

6) Job search skills: indicator variable that equals one if R believes that he/she has the skills to find out about different kinds of jobs

7) Importance of work success: indicator variable that equals one if R believes that success in their eventual work is very important to their future life

8) Importance of steady work: indicator variable that equals one if R believes that being able to find steady work is very important to their future life

9) Depression: indicator variable that equals one if R has felt depressed or very unhappy several times or a lot during the several weeks before the interview.

Table A1. Descriptive statistics of dropouts in Florida who last tested for the GED between 1995 and 1998 (standard deviation in parentheses).

| | Males | Females |
|---|---|---|
| Sample size | 10,255 | 10,327 |
| Percent… | | |
| white | 73.6 | 75.5 |
| black | 8.8 | 8.1 |
| Hispanic | 13.9 | 13.7 |
| other race/ethnicity | 3.7 | 2.8 |
| who obtained a GED | 89.4 | 92.2 |
| with multiple GED attempts | 12.4 | 11.2 |
| who completed less than 8 years of schooling | 1.5 | 1.0 |
| who completed 8 years of schooling | 14.0 | 10.0 |
| who completed 9 years of schooling | 30.8 | 28.5 |
| who completed 10 years of schooling | 34.1 | 39.8 |
| who completed 11 years of schooling | 18.1 | 19.0 |
| who completed 12 years of schooling[a] | 1.5 | 1.7 |
| Median age at the GED test | 17.5 | 17.4 |
| Mean standardized math score | 0.11 | –0.07 |
| | (1.10) | (0.95) |
| Mean quarters of work experience by the 12th quarter after the GED test | 5.2 | 5.6 |
| | (3.5) | (3.4) |
| Mean positive quarterly earnings 3rd year after testing for those in lowest math quartile | 2456 | 2102 |
| | (1745) | (1487) |
| Mean positive quarterly earnings 3rd year after testing for those in highest math quartile | 2843 | 2588 |
| | (1906) | (1733) |

a. Individuals could have completed 12 years of schooling without obtaining a high school diploma.

Table A2. Discounted Present Value of Benefits of a Skills-Enhancing Intervention Under Different Assumptions Regarding (1) Size of Program Impact on Skills, (2) Discount Rate, and (3) Annual Rate of Productivity Growth in the Economy.

| | Discount Rate | Annual Productivity Growth Rate | | |
|---|---|---|---|---|
| | | 0 | 1 | 2 |
| Panel A: 0.10 SD Program Impact | | | | |
| | 0.02 | 8412 | 11020 | 14576 |
| | 0.03 | 6537 | 8456 | 11049 |
| | 0.04 | 5155 | 6585 | 8498 |
| | 0.05 | 4124 | 5202 | 6632 |
| | 0.06 | 2750 | 3386 | 4213 |
| Panel B: 0.25 SD Program Impact | | | | |
| | 0.02 | 21031 | 27550 | 36441 |
| | 0.03 | 16343 | 21140 | 27623 |
| | 0.04 | 12888 | 16462 | 21247 |
| | 0.05 | 10311 | 13007 | 16508 |
| | 0.06 | 6875 | 8466 | 10533 |

Table 1. GED math score regressions (standard errors in parentheses).[a,b]

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Years of schooling | — | 0.184** | 0.189** | 0.167** |
| | | (0.007) | (0.007) | (0.007) |
| Black | — | — | –0.69** | –0.65** |
| | | | (0.02) | (0.02) |
| Hispanic | — | — | –0.20** | –0.19** |
| | | | (0.02) | (0.02) |
| Other race/ethnicity | — | — | –0.03 | –0.03 |
| | | | (0.04) | (0.04) |
| More than one GED attempt | — | — | — | –0.57** |
| | | | | (0.02) |
| Female | –0.18** | –0.21** | –0.21** | –0.21** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Age at GED test | –0.09** | –0.18** | –0.15** | –0.12** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Constant | 1.61** | 1.42** | 1.06** | 0.75** |
| | (0.20) | (0.20) | (0.20) | (0.20) |
| $R^2$ | 0.011 | 0.042 | 0.082 | 0.116 |
| N | 20,582 | 20,582 | 20,582 | 20,582 |

a. All regressions also control test cohort fixed effects.
b. ~ = 0.10 α-level, * = 0.05 α-level, ** = 0.01 α-level.

Table 2. Log quarterly earnings regressions for GED candidates (standard errors in parentheses).[a,b]

| | (1) | (2) | (3) |
|---|---|---|---|
| Math | 0.074** | 0.064** | 0.063** |
| | (0.007) | (0.007) | (0.007) |
| $Math^2$ | -0.013** | -0.010** | -0.010** |
| | (0.004) | (0.004) | (0.004) |
| Years of schooling | 0.045** | 0.049** | 0.048** |
| | (0.006) | (0.006) | (0.006) |
| Black | — | –0.25** | –0.25** |
| | | (0.02) | (0.02) |
| Hispanic | — | 0.06** | 0.06** |
| | | (0.02) | (0.02) |
| Other race/ethnicity | — | –0.10** | –0.10** |
| | | (0.03) | (0.03) |
| More than one GED attempt | — | — | –0.03 |
| | | | (0.02) |
| Quarters of work experience | 0.200** | 0.198** | 0.198** |
| | (0.005) | (0.005) | (0.005) |
| Quarters of work experience squared | –0.008** | –0.008** | –0.008** |
| | (0.001) | (0.001) | (0.001) |
| Female | –0.07** | –0.07 ** | –0.08 ** |
| | (0.01) | (0.01) | (0.01) |
| Age at GED test | 0.09** | 0.09** | 0.09** |
| | (0.01) | (0.01) | (0.01) |
| Possesses a GED | 0.066** | 0.045~ | 0.043~ |
| | (0.025) | (0.023) | (0.025) |
| Constant | 4.54** | 4.47** | 4.46** |
| | (0.18) | (0.17) | (0.17) |
| $R^2$ | 0.100 | 0.104 | 0.104 |
| N | 20,582 | 20,582 | 20,582 |

a. All regressions also control for the year and quarter when earnings were measured and test cohort fixed effects.
b. ~ = 0.10 $\alpha$-level, * = 0.05 $\alpha$-level, ** = 0.01 $\alpha$-level.

Table 3. Distribution across math score quartiles by gender and race/ethnicity.

| | Column Percentages | | | | | |
|---|---|---|---|---|---|---|
| | Males | | | Females | | |
| | White | Black | Hispanic | White | Black | Hispanic |
| 1st math score quartile | 20.9 | 50.0 | 26.2 | 26.3 | 54.0 | 33.3 |
| 2nd math score quartile | 20.9 | 22.4 | 22.1 | 24.7 | 21.1 | 26.5 |
| 3rd math score quartile | 30.0 | 18.7 | 28.5 | 27.8 | 16.9 | 25.3 |
| 4th math score quartile | 28.2 | 8.9 | 23.2 | 21.2 | 8.0 | 14.9 |
| Column percent | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

Table 4. Log hourly wage regressions using individuals in the NLSY who were age 16-18 in 1980 when they took the AFQT.[a,b]

| | Log hourly wages 1981-1983 (1) | Log hourly wages 1981-1990 (2) |
|---|---|---|
| AFQT | 0.031<br>(0.021) | 0.013<br>(0.022) |
| AFQT X Time trend | — | 0.009*<br>(0.004) |
| Time trend | — | –0.007<br>(0.006) |
| Years of schooling | –0.02<br>(0.01) | –0.007<br>(0.008) |
| Black | 0.03<br>(0.04) | 0.01<br>(0.03) |
| Hispanic | 0.04<br>(0.04) | 0.01<br>(0.03) |
| Other race/ethnicity | 0.13<br>(0.08) | 0.05<br>(0.06) |
| Work experience | 0.10*<br>(0.05) | 0.08**<br>(0.01) |
| Female | –0.16**<br>(0.03) | –0.17**<br>(0.02) |
| Age in 1979 | 0.05*<br>(0. 02) | 0.04*<br>(0. 02) |
| Variables in the *O* vector[c] | Yes | Yes |
| Constant | 5.74<br>(0.36) | 6.26<br>(0.27) |
| Sample size | 750 | 923 |
| $R^2$ | 0.109 | 0.183 |

a. ~ = 0.10 $\alpha$-level, * = 0.05 $\alpha$-level, ** = 0.01 $\alpha$-level.

b. Both regressions also control for whether or not in enrolled in school, region of the country (4 regions), work experience squared (both estimates are very close to zero), the local unemployment rate, and the year in which wages are measured.

c. Including mother's education level, fathers education level, indicator for mother working, indicator for father working, indicators for the presence of magazines, newspapers, and/or a library card in the home, number of siblings, and an indicator for whether English was the primary language of the home. All variables pertain to when the respondent was age 14.

Figure 2. Distribution of unstandardized GED math scores.

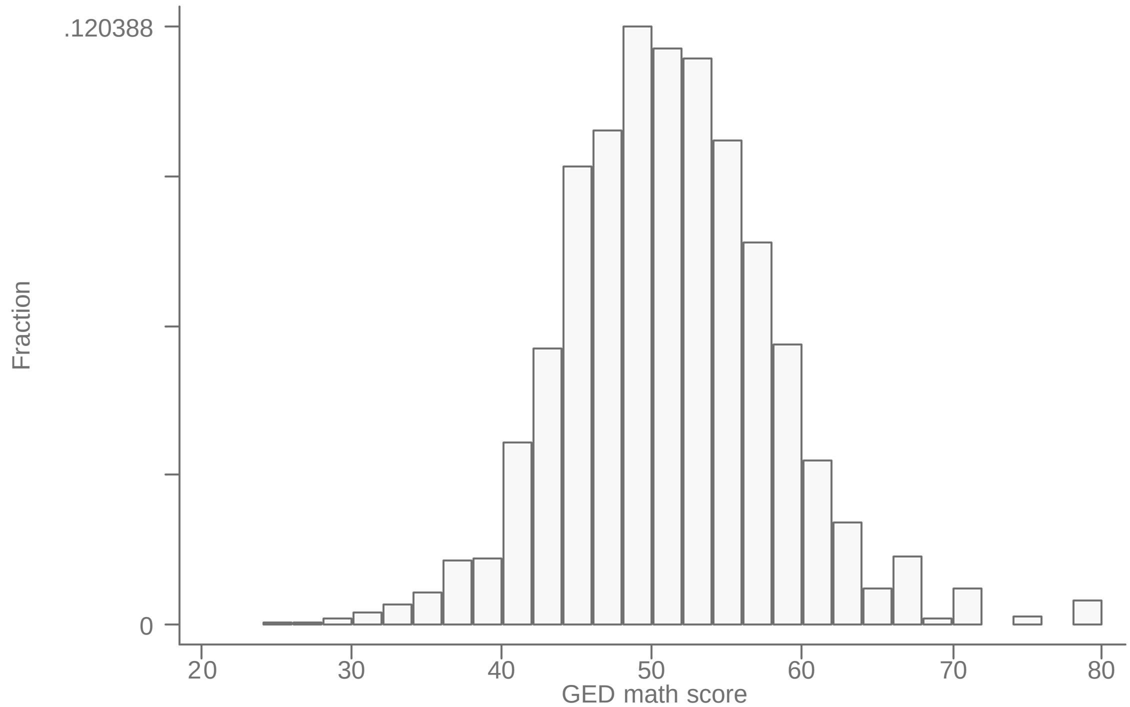


Figure 3a. Mean quarterly earnings of male dropouts by upper and lower quartile of the GED math score distribution for quarters 1-12 after the last GED attempt.

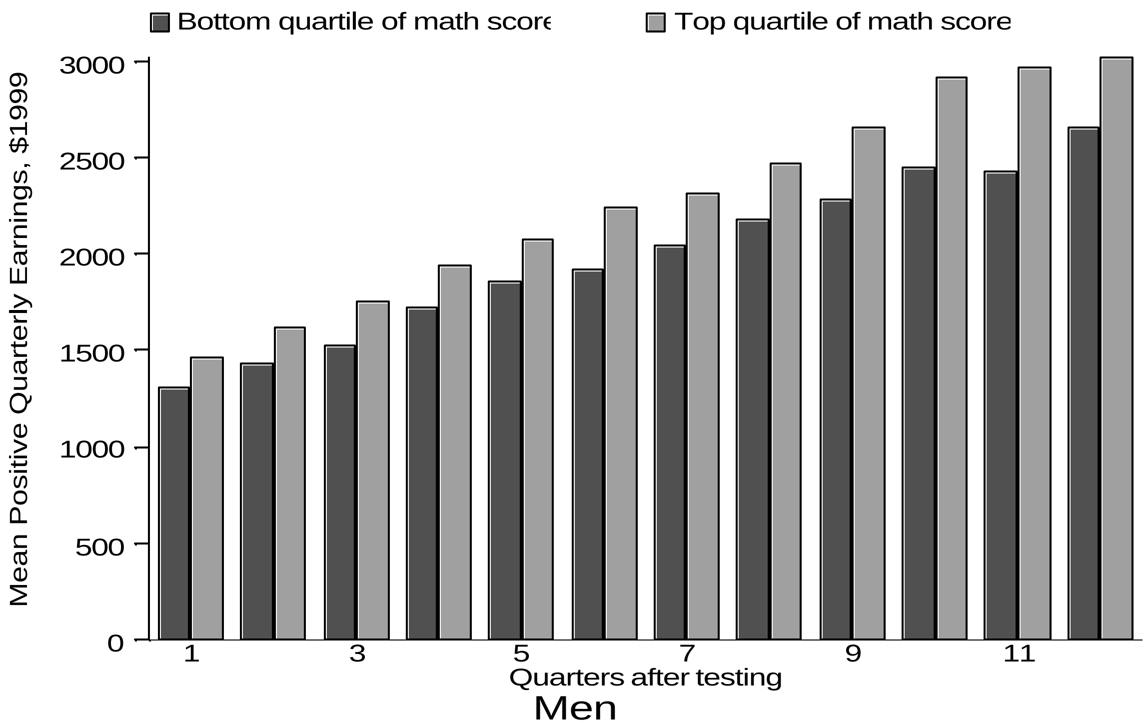



Figure 3b. Mean quarterly earnings of female dropouts by upper and lower quartile of the GED math score distribution for quarters 1-12 after the last GED attempt.

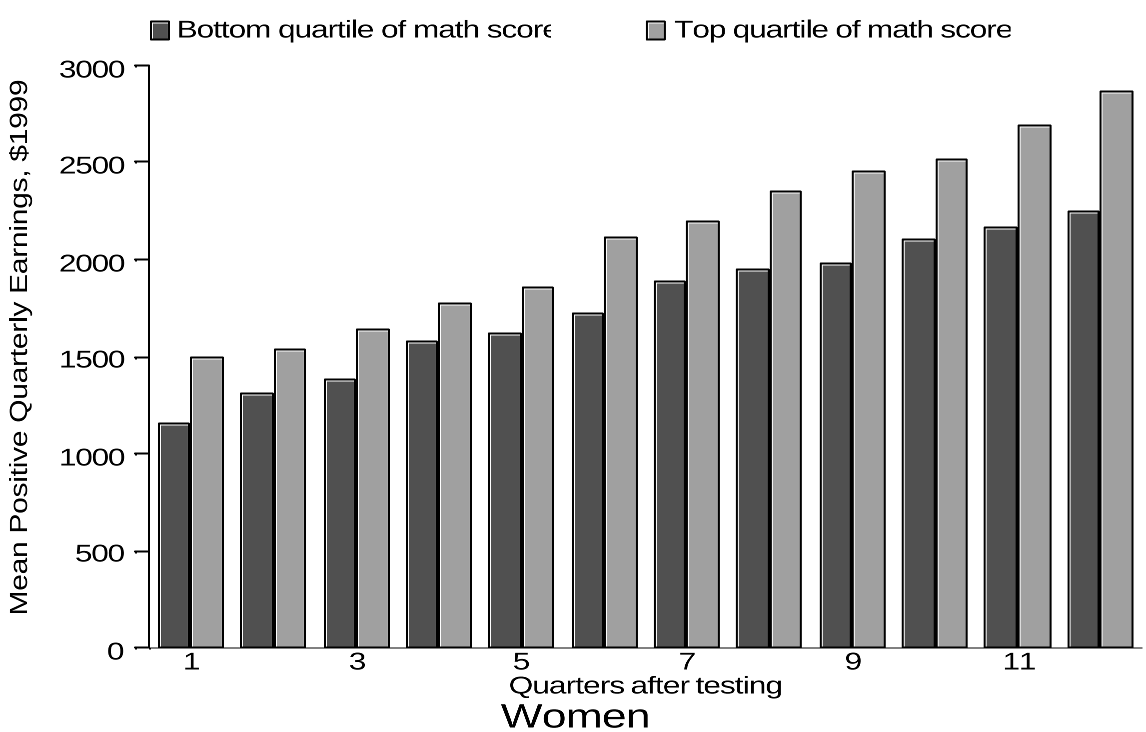


Figure 4. Distribution of AFQT scores for NLSY dropouts.

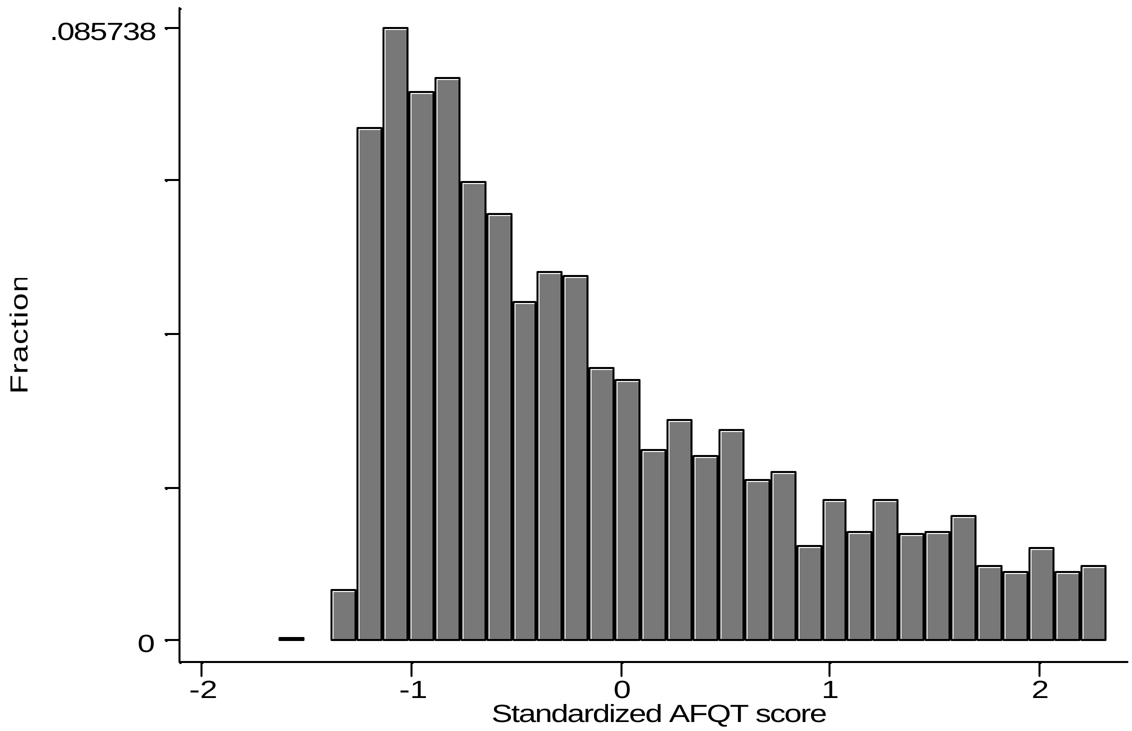
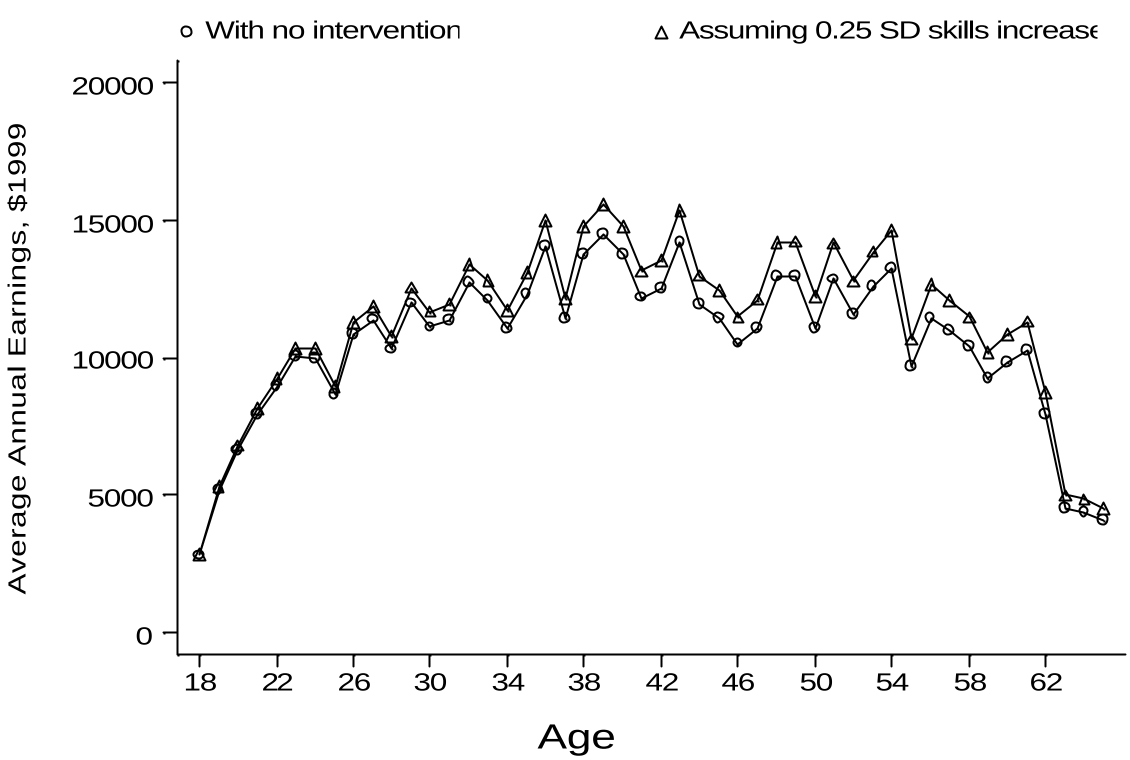



Figure 5. 1999 CPS-based age-earnings profiles of dropouts (lower profile) compared to the augmented (upper) age-earnings profile assuming an increase in the basic cognitie skills of 18 year-old dropouts of 0.25 of a standard deviation.



References


Altonji, Joseph G. 1994. "The Effects of High School Curriculum on Education and Labor Market Outcomes." *The Journal of Human Resources* 30, no. 3, 409-438.

Altonji, Joseph G. and Charles R. Pierret. 1996. Employer Learning and the Signaling Value of Education. Cambridge, MA: National Bureau of Economic Research Working Paper #5438.

Angrist, Joshua D. and Alan B. Krueger. 1991. "Does Compulsory School Attendance Affect Schooling and Earnings?" *Quarterly Journal of Economics* 106, no. 4, 979-1014.

Ashenfelter, Orley and Alan Krueger. 1994. "Estimates of the Economic Returns to Schooling from a New Sample of Twins." *American Economic Review* 84, no. 5, 1157-1173.

Ashenfelter, Orley and Cecilia Elena Rouse. 1998. "Income, Schooling, and Ability: Evidence from a New Sampling of Identical Twins." *Quarterly Journal of Economics* 113, no. 1, 253-284.

Autor, David H., Frank Levy, and Richard J. Murnane. 2001a. "The Skill Content of Recent Technological Change: An Empirical Exploration." *NBER Working Paper No. W8337*.

________. 2001b. "Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank." *Industrial and Labor Relations Review* Forthcoming.

Bartel, Ann P. and Nachum Sicherman. 1997. "Technological Change and Wages: An Inter-Industry Analysis." *National Bureau of Economic Research Working Paper: 5941*.

Becker, Gary S. 1964. *Human Capital: A Theoretical and Empirical Analysis*. New York: Columbia University Press.

Behrman, Jere R. and Mark R. Rosenzweig. 1999. "'Ability ' Biases in Schooling Returns and Twins: A Test and New Estimates." *Economics of Education Review* 18, no. 2, 159-167.

Berman, Eli, John Bound, and Zvi Griliches. 1994. "Changes in the Demand for Skilled Labor Within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufacturing." *Quarterly Journal of Economics* 109, no. 2, 367-97.

Boissiere, M., J.B. Knight, and R.H. Sabot. 1985. "Earnings, Schooling, Ability, and Cognitive Skills." *The American Economic Review* 75, no. 5, 1016-1030.

Cameron, Stephen V. and James J. Heckman. 1993. "The Nonequivalence of High School Equivalents." *Journal of Labor Economics* 11, no. 1, 1-47.

Cawley, John, Karen Conneely, James J. Heckman, and Edward Vytlacil. 1997. Cognitive Ability, Wages, and Meritocracy. In *Intelligence, Genes, and Success: Scientists Respond to The Bell Curve*, ed. Bernie Devlin, Stephen Fienberg, Daniel Resnick and Kathryn Roeder. New York: Springer Verlag.

Cawley, John, James J. Heckman, and Edward Vytlacil. 2001. "Three Observations on Wages and Measured Cognitive Ability." *Labour Economics* 8, 419-422.

Farber, Henry S. and Robert Gibbons. 1996. "Learning and Wage Dynamics." *Quarterly Journal of Economics* November, 1007-1047.

Glazerman, Steven, Peter Z. Schochet, and John Burghardt. 2000. *National Job Corps Study: The Impacts of Job Corps on Participants' Literacy Skills*. Washington, D.C.: U.S. Department of Labor, Employment and Training Administration.

Griliches, Zvi. 1977. "Estimating the Returns to Schooling: Some Econometric Problems." *Econmetrica* 45, no. 1, 1-22.

Griliches, Zvi and William M. Mason. 1979. "Education, Income, and Ability." *Journal of Political Economy* 87, no. 5, S37-S64.

Heckman, James J. 2000. "Policies to Foster Human Capital." *Research in Economics* 54, no. 1, 3-56.

Heckman, James J. and Edward Vytlacil. 2001. "Identifying the Role of Cognitive Ability in Explaining the Level of Change in the Returns to Schooling." *Review of Economics and Statistics* 83, no. 1, 1-12.

Herrnstein, Richard J. and Charles Murray. 1994. *The Bell Curve.* New York: Free Press.

Ishikawa, Mamoru and Daniel Ryan. 2002. "Schooling, Basic Skills, and Economic Outcomes." *Economics of Education Review* 21, no. 3, 231-243.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan. 1993. "Earnings Losses of Displaced Workers." *American Economic Review* 83, no. 4, 685-709.

Kane, Thomas J. and Cecilia Rouse. 1995. "Labor Market Returns to Two-Year and Four-Year College." *American Economic Review* 85, no. 3, 600-614.

Katz, Lawrence F. and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *The Quarterly Journal of Economics* 107, no. Feb. 1992, 33-78.

Kornfeld, Robert and Howard Bloom. 1999. "Measuring Program Impacts on Earnings and Employment: Do Unemployment Insurance Wage Records Agree with Survey Reports of Individuals?" *Journal of Labor Economics* 17, no. 1, 168-197.

Krueger, Alan. 1998. "Reassessing the View that American Schools Are Broken." *Economic Policy Review* 4, no. 1, 29-43.

________. 2000. "Economic Considerations and Class Size." *Unpublished manuscript.*

Mane, Ferran. 1999. "Trends in the Payoof to Academic and Occupation-Specific Skills: The Short and Medium Run Returns to Academic and Vocational High School Courses for Non-College-Bound Students." *Economics of Education Review* 18, 417-437.

Mincer, Jacob. 1958. "Investment in Human Capital and the Personal Income Distribution." *Journal of Political Economy* 66, no. 4, 281-302.

Murnane, Richard J. and Frank Levy. 1996a. *Teaching the New Basic Skills*. New York: Free Press.

________. 1996b. "With What Skills are Computers a Complement?" *American Economic Review* 86, no. 2, 258-262.

Murnane, Richard J., John B. Willett, Yves Duhaldeborde, and John H. Tyler. 2000. "How Important Are the Cognitive Skills of Teenagers in Predicting Subsequent Earnings?" *Journal of Policy Analysis and Management* 19, no. 4, 547-568.

Murnane, Richard J., John B. Willett, and Frank Levy. 1995. "The Growing Importance of Cognitive Skills in Wage Determination." *Review of Economics and Statistics* 77, no. 2, 251-66.

Osterman, Paul. 2001. "Work Reorganization in an Era of Restructuring: Trends in Diffusion and Effects on Employee Welfare." *Industrial and Labor Relations Review* 53, no. 2, 179-196.

Spence, Michael. 1973. "Job Market Signaling." *Quarterly Journal of Economics* 87, 355-374.

Taubman, Paul. 1976. "The Determinants of Earnings: Genetics, Family, and Other Environments; A Study of White Male Twins." *American Economic Review* 66, no. 5, 858-870.

Taubman, Paul J. and Terence J. Wales. 1973. "Higher Education, Mental Ability, and Screening." *The Journal of Political Economy* 81, no. 1, 28-55.

Tyler, John H., Richard J. Murnane, and John B. Willett. 2000a. "Do the Cognitive Skills of Dropouts Matter in the Labor Market?" *Journal of Human Resources* 35, no. 4, 748-754.

________. 2000b. "Estimating the Labor Market Signaling Value of the GED." *Quarterly Journal of Economics* CXV, no. 2, 431-468.

________. 2001. "Who Benefits from a GED? Evidence for Females from High School and Beyond." *Brown University Department of Economics Working Paper No. 01-35*.